# Temporal and external validation of a prediction model for adverse outcomes among inpatients with diabetes

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### Running title

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## ABSTRACT

### Aim

National audits have highlighted suboptimal care for inpatients with diabetes. There is a need to design care pathways enabling patients to be seen by the right team at the right time; evidence suggests this will lead to improvements in patient outcomes such as mortality and length of stay. We previously developed a prediction model using data from University Hospitals Birmingham (UHB) to identify inpatients with diabetes at high risk of adverse outcome (mortality or excessive length of stay), which could facilitate more effective management of these patients by the care team. The aim of this study was to temporally and externally validate the model to demonstrate its applicability to other hospital populations within the UK.

### Methods

Temporal validation was performed using data from UHB; external validation was performed using data from Heart of England Foundation Trust (HEFT) and Ipswich Hospital. All adult inpatients with diabetes were included. Variables included in the model were age; gender; ethnicity; admission type; Intensive Therapy Unit admission; insulin therapy; albumin; sodium; potassium; haemoglobin; C-Reactive Protein; estimated Glomerular Filtration Rate; neutrophil count. Adverse outcome was defined as excessive length of stay or death.

### Results

Model discrimination in the temporal and external validation datasets was good. In temporal validation using data from UHB, AUC was 0.797 (95% CI 0.785-0.810); sensitivity was 70% (95% CI 67-72) and specificity was 75% (95% CI 74-76). In external validation using data from HEFT, AUC was 0.758 (95% CI 0.747-0.768); sensitivity was 73% (95% CI 71-74) and specificity was 66% (95% CI 65-67). In external validation using data from Ipswich, AUC was 0.736 (95% CI 0.711-0.761); sensitivity was 63% (95% CI 59-68) and specificity was 69%

(95% CI 67-72). These results are comparable to the internally validated model derived at UHB.

**Conclusion**

The prediction model to identify patients with diabetes at high risk of developing an adverse event while in hospital performed well in temporal and external validation. The externally validated prediction model is a novel tool that can be used to improve care pathways for inpatients with diabetes. Further research to assess clinical utility is needed.

**Keywords**

Diabetes Management; Inpatients; Inpatient Management; Secondary Care; Prediction Model; Adverse Outcomes; Statistical Models; Diabetes Complications; Health Care Delivery

**What's new?**

- National audits have highlighted suboptimal care for inpatients with diabetes. Evidence suggests targeted review of hospitalised patients with diabetes by a specialist team, utilising electronic triggers, could improve clinical outcomes. To date, no externally validated tool to identify inpatients with diabetes at risk of adverse outcome has been published.
- In this study we temporally and externally validated a prediction model to identify inpatients with diabetes who are at high risk of developing adverse outcomes.
- Model performance was found to be optimal and sufficient for further evaluation in clinical practice, where it may be used to prevent harm, improve clinical outcomes, and prioritise care for inpatients with diabetes.

## Introduction

Diabetes mellitus is the most common documented comorbidity in a hospital setting, affecting 17% of all adult admissions.[1] Hospitalised patients with diabetes have high infection rates,[2-5] longer length of stay (1-3 more days compared to patients without diabetes)[6-8] and increased mortality (6.4% higher).[9] Reasons for poor clinical outcomes are less well understood but poor glycaemic control and foot disease have been implicated as potential reasons.[10-13] In 2009/10, people with diabetes accounted for 11% of NHS expenditure on in-hospital care, totalling around £2.5billion.[14]

Inpatients with diabetes do not receive optimal care: only 30% have their feet examined in the first 24 hours and only 60% of those admitted with active foot disease are referred to multidisciplinary foot care teams within the first 24 hours of admission,[1] despite these standards being recommended by NICE.[15] Furthermore, antidiabetes medication errors (occurring in 21% of patient admissions)[1] may result in patient harm, including death.[16] Patient surveys and qualitative studies have also highlighted issues around incorrect medications, disempowerment, poor meal timing and choice, and inadequate specialist team input into diabetes care.[1,17]

Diabetes specialist teams for inpatient diabetes care may improve patient outcomes and reduce length of stay.[18-21] But with rising numbers of inpatients with diabetes there is a need to upskill ward staff to manage generic needs of people with diabetes and only refer to specialist team for ‘complex needs’. The ‘ThinkGlucose’ campaign[22] recommended criteria for inpatient referral to diabetes specialist teams, but, despite widespread campaigning, only 69% of patients meeting these criteria are seen by the diabetes specialist team.[1] Very little is known regarding whether referrals were timely and if the reason for referral could have been avoided by implementing optimal care at an earlier stage.

There is a need to develop tools to identify patients in need of diabetes specialist team review early during their admission, preferably before they experience an adverse outcome. Such tools could be incorporated into the electronic medical record.

Using data from University Hospitals Birmingham NHS Foundation Trust, our research team has previously developed and internally validated a prediction model that identifies hospitalised patients with diabetes at risk of adverse outcome while in hospital (mortality or excessive length of stay).[23] Unique features of the prediction model are: it does not require the reason for admission or information on comorbidities, as routinely available data including blood results are used to predict risk; and it has the ability to identify patients at risk of adverse outcome within the first 24 hours of admission.

The aim of this study was to temporally and externally validate this prediction model, in order to determine whether it performs equally well in more recent data and in other hospital settings before trialling for clinical practice.

## Methods

### Setting and data sources

The prediction model was developed using data from University Hospitals Birmingham NHS Foundation Trust (UHB) from 2007 to 2010.[23] Temporal validation was carried out using inpatient data from 1st January to 31st December 2014 from University Hospitals Birmingham NHS Foundation Trust (UHB). External validation was carried out using inpatient data from 1st January to 31st December 2014 from Heart of England NHS Foundation Trust (HEFT) and inpatient data from 1st January to 30th June 2014 from Ipswich Hospital.

UHB is a tertiary hospital in the West Midlands with over 1200 beds, providing secondary care to an ethnically diverse population. HEFT is a large hospital trust, comprised of several hospitals across the West Midlands (Heartlands, Good Hope and Solihull), with a total of more

than 1550 beds; the trust serves an ethnically and socio-economically diverse range of communities. Ipswich Hospital is located in the East of England; it is a district hospital with approximately 800 beds, and provides secondary care to a slightly older, less deprived and less ethnically diverse population.

**Participants**

All patients with diabetes aged 16 and over were included in the analysis. For HEFT, data was only available for patients aged 18 years and over.

**Outcome definition**

Adverse outcome was a composite of excessive length of stay or death.[23] Excessive length of stay was defined as an excess length of stay greater than the 75$^{th}$ centile for all admissions for people with diabetes. Excess length of stay was defined as the difference between the actual length of stay for the diabetic inpatient admission and the median length of stay calculated in all inpatients with diabetes admitted in the same primary diagnosis category. In sensitivity analysis, median length of stay was calculated in inpatients without diabetes (UHB only; this data was not available for HEFT and Ipswich). Primary diagnosis category was defined using the 260 group categories in the Healthcare Research and Quality clinical classification software (CCS).[24]

**Definitions of variables**

Diabetes was defined using discharge diagnostic codes and prescription data. The diagnostic codes used to indicate diabetes were International Classification of Diseases version 10 (ICD-10) codes E10–E14 or any of their sub-classifications. Additionally, patients were categorised as having diabetes if they were on any of type of insulin, sulphonylurea, biguanide or other antidiabetes drug, excluding patients on metformin alone with a discharge diagnostic code for

polycystic ovarian syndrome or patients who received short- or rapid-acting insulin alone.[25] All inpatients with diabetes were included irrespective of primary diagnosis.

The variables included in the model were: age; sex; ethnicity; admission type (elective or emergency); intensive therapy unit (ITU) admission (binary); insulin therapy (binary); presence/absence of foot disease (binary); and the following clinical pathology test results: albumin, sodium, potassium, haemoglobin, C-Reactive Protein (CRP), estimated Glomerular Filtration Rate (eGFR), neutrophil count. Insulin therapy was defined as one or more prescription for insulin during the admission; this data was not available for Ipswich, therefore insulin prescription prior to admission was used. Presence of foot disease was identified using both discharge diagnostic codes and OPCS Classification of Interventions and Procedures codes recorded at any time during the admission.[13] In instances where a patient had multiple blood tests during a single admission, the earliest test result for the admission was used.

Normal blood test results were defined as follows: albumin ≥ 35 g/L; sodium 135–144 mmol/L; potassium 3–5.9 mmol/L; haemoglobin ≥ 12 g/dL; CRP 0–9 mg/L; eGFR ≥ 90 mL/min/1.73 $m^2$; neutrophil count $<7.9 \times 10^9$/L.

**Definition of model**

Coefficients of the logistic regression model are presented in Supplementary Table 1.

**Analysis**

For patients with multiple admissions, a single, randomly selected admission was included in the analysis; a sensitivity analysis was carried out including all admissions. Data were complete for all variables except clinical pathology (blood) test results. Missing clinical pathology test results were replaced using multiple imputation (10 imputations); this was performed using chained equations and predictive mean matching. In additional sensitivity analysis, missing test

results were replaced with values in the normal range to better reflect use of the model in a hospital setting.

### Performance assessment

Model discrimination was assessed by plotting a receiver operating characteristic (ROC) curve and calculating area under the curve (AUC, or Harrell's C-statistic). Sensitivity, specificity, and positive and negative predictive values were calculated at a ≥ 25% predicted chance of adverse outcome; this was found to be the optimal threshold, at which the sum of sensitivity and specificity was maximal (Youden's index), during development of the model. Test statistics generated from the 10 imputed datasets were combined using Rubin's rule. Model calibration was assessed by plotting predicted probabilities of outcome against observed probabilities of outcome, by decile, with overlaid LOWESS (locally weighted scatterplot smoothing) curve.

## Results

### Temporal validation

6,533 inpatients with diabetes contributing to a total of 11,019 hospital admissions at UHB were included in the temporal validation analysis. 27.5% (n = 1,797) of these patients had an adverse outcome: 1,529 patients had an excessive length of stay, 164 died, and 104 had an excessive length of stay ending in death. Baseline patient characteristics are presented in Table 1 (see also Supplementary Table 2). Patient characteristics in the UHB temporal validation dataset (2014) were comparable to those in the original UHB model development dataset (2007–2010), with the exception of the proportion of patients prescribed insulin, which had decreased from 67.9% and 47.8% (2007–2010) to 47.5% and 20.6% (2014) in patients with and without adverse outcome respectively. Additionally, blood test results were more complete in the 2014 data (Supplementary Table 3).

In temporal validation, replacing missing values using multiple imputation, model discrimination was good: AUC was 0.797 (95% CI 0.785–0.810). At a threshold of ≥ 25% predicted probability of adverse event, sensitivity was 69.5% (95% CI 67.3–71.6) and positive predictive value (PPV) was 51.3% (95% CI 49.2–53.3) (Table 2).

In the three sensitivity analyses, replacing missing values with values in the normal range, calculating median length of stay in non-diabetic inpatients, and using all admissions for inpatients with diabetes (rather than just a single randomly selected admission for each patient) made very little difference to model performance (Table 2, Figure 2, and Supplementary Tables 4 and 5).

Model calibration was good, with the LOWESS curve in close proximity to the 45 degree line, i.e. predicted probabilities were similar to observed probabilities (Figure 1d).

**External validation**

10,690 inpatients with diabetes contributing to a total of 16,568 hospital admissions at HEFT, and 1,885 patients contributing to a total of 2,554 hospital admissions at Ipswich were included in the external validation analyses. In the HEFT dataset, 27.8% (n = 2,973) of patients had an adverse outcome: 2,423 patients had an excessive length of stay, 301 died, and 249 had an excessive length of stay ending in death. In the Ipswich dataset, 27.4% (n = 517) of patients had an adverse outcome: 425 patients had an excessive length of stay, 46 died, and 46 had an excessive length of stay ending in death. Baseline patient characteristics are presented in Table 1 (see also Supplementary Table 2). In both the HEFT and Ipswich datasets, there were more emergency admissions and fewer ICU admissions compared to UHB. Fewer HEFT patients had foot disease. Insulin treatment rates were lower at Ipswich, with little difference between rates in patients with or without adverse outcome.

In the HEFT external validation dataset, replacing missing values using multiple imputation, AUC was 0.758 (95% CI 0.747–0.768). At a threshold of ≥ 25% predicted probability of adverse event, sensitivity was 72.6% (95% CI 70.9–74.2) and PPV was 45.1% (95% CI 43.7–46.5) (Table 2).

In the Ipswich external validation dataset, replacing missing values using multiple imputation, AUC was 0.736 (95% CI 0.711–0.761). At a threshold of ≥ 25% predicted probability of adverse event, sensitivity was 63.4% (95% CI 59.1–67.6) and PPV was 43.8% (95% CI 40.3–47.5) (Table 2).

In two sensitivity analyses, missing values were replaced with values in the normal range, and model performance was assessed in all admissions for inpatients with diabetes (rather than using a single randomly selected admission for each patient); this made little difference to the model performance (Table 2, Figures 1b-c and 2, and Supplementary Table 5).

Model calibration was good in both datasets (Figures 1e-f).

## Discussion

Our previously published model performed well with an AUC of 0.80, 0.76 and 0.74 in UHB, HEFT and Ipswich respectively. It was able to identify (sensitivity) two thirds to three quarters of patients at high risk of adverse outcomes (63% at Ipswich Hospital, 70% at UHB and 73% at HEFT). Among those who were predicted by the model to have an adverse outcome, 44% in Ipswich Hospital, 45% in HEFT and 51% at UHB (positive predictive value) went on to have an adverse event defined as death or excessive length of stay. The results were robust in our sensitivity analyses; performance improved when missing values were replaced with normal values, which better reflects implementation in a clinical setting.

Prediction models can become outdated with change in population demography, better linkage of data systems, better therapeutic options and care pathways, and improvement in data

recording. However, model performance at UHB was similar after nearly 5 years, with an AUC of 0.802 (95% CI 0.795–0.808) and 0.804 (95% CI 0.792–0.816)[23] in the development and temporal validation datasets respectively. Specificity increased from 70% in the derivation dataset to 75% in the temporal validation dataset, and PPV remained similar, changing from 49% to 51%. Sensitivity was lower at 70% in temporal validation compared to 76% in the derivation dataset. This can be attributed in part to improved linkage of Electronic Medical Record (EMR) data to Patient Administrative System data in recent years (> 95% compared to 77% previously[25]). This means patients who were less ill may not have been included in the model development dataset as they would have been discharged before being entered into the EMR, leading to some dissimilarity between the patient cohorts.

Model performance in Ipswich Hospital was slightly inferior. This may be explained by the fact that only data from the first six months of the calendar year was available; the population was less ethnically diverse compared to the other two hospitals; and the definition of insulin differed. The observed differences in insulin use may be attributable to a difference in the prescription information used (insulin prior to admission rather than during) and to the method of data recording (use of in-house insulin recording rather than electronic prescription data, as at UHB and HEFT). However, the performance parameters were still comparable to many clinically utilised prediction models such as the Rockall score for outcomes of upper gastrointestinal bleed.[26]

Overall, the results of this analysis demonstrate that the model is both temporally and externally valid: it performed well in both more recent data from the original hospital (UHB) and in other hospitals with sociodemographically different inpatient populations (HEFT, Ipswich). This indicates that the model is applicable in diverse and varying hospital populations within the UK.

The strengths of the study include external validation across two distinctly different hospital settings, datasets with large number of patients and events, robust methodology including number of sensitivity analyses, and being the first study to derive and validate a prediction model to identify adverse events in hospitalised patients with diabetes based on routinely collected data close to the time of admission. Only two other algorithms that aim to identify patients at risk of hypoglycaemia exist for inpatients with diabetes, but these were not externally validated.[27-28] However, validation is limited to hospitals in the United Kingdom, and data from Ipswich Hospital had limitations that prevented us from optimally demonstrating the performance in a District General Hospital setting.

One of the unique features of the model is that it utilises routinely collected data on admission and can therefore be incorporated into EMR without any additional information needs. However, the model could only be incorporated where there are robust EMR; currently only a third of UK hospitals are fully utilising EMR, while a further 31% are making partial use of EMR.[1] Nevertheless the UK government has encouraged hospitals to procure EMR and replace paper-based medical records within the next few years.[29] Therefore it is the right time to develop and evaluate novel tools that could result in better clinical outcomes and healthcare efficiency.

The model has potential clinical utility and could help shape care pathways for hospitalised patients with diabetes. We propose to develop electronic care pathways and test direct and indirect triggers that could alert diabetes specialist teams or other health professionals to take timely actions. Direct triggers will include alerts for recurrent or severe hypoglycaemia, insulin infusions over 48 hours and persistent hyperglycaemia. The prediction model will serve as an indirect trigger and will aim to identify patients at high risk of adverse event (Figure 3). If the model were implemented, about half of people with diabetes flagged up by a system like this would experience an adverse outcome. Furthermore most of those who will experience an

adverse outcome would be flagged up. This suggests the model might be useful in identifying those individuals who might benefit from additional input. Clinical judgement might play a further role in identifying those flagged up who were most likely to benefit from input. However, it should be noted that, at present, there is a lack of strong evidence regarding whether or not specialist inpatient diabetes teams can reduce mortality; this is an area that requires further research.

One criticism of the model is that it may identify ill patients who might not particularly benefit from review by the diabetes specialist team. Another criticism is that most covariates and the outcomes in the model are not diabetes-specific, and the model may therefore perform well in other chronic conditions to predict length of stay and mortality. However, we have shown parameters in the model can predict hypoglycaemia[28] and therefore it is reasonable to hypothesize that a care pathway with risk stratification can enable harm reduction and better clinical end points for inpatients with diabetes. For example, an algorithm for hypoglycaemia developed and implemented in a hospital in the United States resulted in 68% reduction in severe hypoglycaemic episodes.[27]

## Conclusion

The prediction model to identify patients with diabetes at high risk of developing an adverse outcome while in hospital performed well when externally validated. The model now needs to be tested for clinical utility in hospitalised patients with diabetes in England. If found to be of clinical benefit, it should be further externally validated in other countries with EMR before implementation in their hospital setting.

## Figure legends

Figure 1. ROC curves for a. UHB (temporal validation), b. HEFT (external validation), and c. Ipswich (external validation); and calibration plots for d. UHB, e. HEFT, and f. Ipswich (replacing missing data with values in the normal range).

Figure 2. Confusion matrices showing actual and predicted numbers of adverse outcomes for a. UHB, b. HEFT, and c. Ipswich (replacing missing data with values in the normal range).

Figure 3. Proposed electronic triggers enhanced care pathway for hospitalised patients with diabetes.

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## Competing interests

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## Contribution

KN developed the internally validated model. NA carried out temporal and external validation. SM advised on the statistical analysis. NA and KN wrote the first draft of the paper; all authors contributed to the interpretation of the results and to the revision of the manuscript.

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**Table 1. Baseline characteristics for patients with and without adverse outcome in each of the three hospital datasets**

| Patient characteristics | UHB (temporal validation) | | HEFT (external validation) | | Ipswich (external validation) | |
|---|---|---|---|---|---|---|
| | No adverse outcome (n = 4736) | Adverse outcome (n = 1797) | No adverse outcome (n =7716 ) | Adverse outcome (n = 2974) | No adverse outcome (n = 1368) | Adverse outcome (n = 517) |
| Age category n (%) | | | | | | |
| 16-44* | 462 (9.8) | 77 (4.3) | 870 (11.3) | 116 (3.9) | 115 (8.4) | 4 (0.8) |
| 45-54 | 703 (14.8) | 159 (8.9) | 1000 (13.0) | 190 (6.4) | 118 (8.6) | 26 (5.0) |
| 55-64 | 997 (21.1) | 306 (17.0) | 1484 (19.2) | 348 (11.7) | 181 (13.2) | 52 (10.1) |
| 65-74 | 1183 (25.0) | 450 (25.0) | 1761 (22.8) | 616 (20.7) | 335 (24.5) | 102 (19.7) |
| 75-84 | 1000 (21.1) | 525 (29.2) | 1881 (24.4) | 1045 (35.1) | 399 (29.2) | 195 (37.7) |
| ≥ 85 | 391 (8.3) | 280 (15.6) | 720 (9.3) | 659 (22.2) | 220 (16.1) | 138 (26.7) |
| Sex n (%) | | | | | | |
| Male | 2645 (55.9) | 973 (54.2) | 4037 (52.3) | 1489 (50.1) | 763 (55.8) | 269 (52.0) |
| Female | 2091 (44.2) | 824 (45.9) | 3679 (47.7) | 1485 (49.9) | 605 (44.2) | 248 (48.0) |
| Ethnicity n (%) | | | | | | |
| White | 3105 (65.6) | 1286 (71.6) | 5273 (68.3) | 2251 (75.7) | 1107 (80.9) | 433 (83.8) |
| South Asian† | 1025 (21.6) | 334 (18.6) | 1737 (22.5) | 488 (16.4) | 20 (1.5) | 3 (0.6) |
| Black | 294 (6.2) | 114 (6.3) | 314 (4.1) | 119 (4.0) | 17 (1.2) | 6 (1.2) |
| Other/missing | 312 (6.6) | 63 (3.5) | 392 (5.1) | 116 (3.9) | 224 (16.4) | 75 (14.5) |
| IMD deprivation quintile n (%) | | | | | | |
| Least deprived 1 | 232 (4.9) | 89 (5.0) | 893 (11.6) | 360 (12.1) | 225 (16.5) | 109 (21.1) |
| 2 | 317 (6.7) | 137 (7.6) | 808 (10.5) | 335 (11.3) | 300 (21.9) | 107 (20.7) |
| 3 | 898 (19.0) | 357 (19.9) | 969 (12.6) | 397 (13.4) | 384 (28.1) | 140 (27.1) |
| 4 | 911 (19.2) | 348 (19.4) | 1071 (13.9) | 448 (15.1) | 177 (12.9) | 61 (11.8) |
| Most deprived 5 | 2293 (48.4) | 824 (45.9) | 3947 (51.2) | 1421 (47.8) | 277 (20.3) | 94 (18.2) |
| Unknown | 85 (1.8) | 42 (2.3) | 28 (0.4) | 13 (0.4) | 5 (0.4) | 6 (1.2) |
| Type of admission n (%) | | | | | | |
| Elective | 1299 (27.4) | 253 (14.1) | 1345 (17.4) | 258 (8.7) | 290 (21.2) | 32 (6.2) |
| Emergency | 3437 (72.6) | 1544 (85.9) | 6371 (82.6) | 2716 (91.3) | 1078 (78.8) | 485 (93.8) |
| Modified Charlson comorbidity score n (%) | | | | | | |
| 0 | 2573 (54.3) | 588 (32.7) | 4653 (60.3) | 1084 (36.5) | 734 (53.7) | 172 (33.3) |
| 1 | 840 (17.7) | 331 (18.4) | 1427 (18.5) | 574 (19.3) | 256 (18.7) | 108 (20.9) |
| ≥2 | 1323 (27.9) | 878 (48.9) | 1636 (21.2) | 1316 (44.3) | 378 (27.6) | 237 (45.8) |
| Insulin use n (%) | | | | | | |
| Yes | 974 (20.6) | 854 (47.5) | 1929 (25.0) | 1121 (37.7) | 201 (14.7) | 73 (14.1) |
| No | 3762 (79.4) | 943 (52.5) | 5787 (75.0) | 1853 (62.3) | 1167 (85.3) | 444 (85.9) |
| ITU care n (%) | | | | | | |
| Yes | 132 (2.8) | 350 (19.5) | 25 (0.3) | 82 (2.8) | 19 (1.4) | 34 (6.6) |
| No | 4604 (97.2) | 1447 (80.5) | 7691 (99.7) | 2892 (97.2) | 1349 (98.6) | 483 (93.4) |
| Foot disease n (%) | | | | | | |
| Yes | 332 (7.0) | 275 (15.3) | 273 (3.5) | 211 (7.1) | 90 (6.6) | 79 (15.3) |
| No | 4404 (93.0) | 1522 (84.7) | 7443 (96.5) | 2763 (92.9) | 1278 (93.4) | 438 (84.7) |

*For HEFT, data was only available for adults aged 18 years and over. †South Asian: Bangladeshi, Indian, Pakistani. IMD: Index of Multiple Deprivation. ITU: Intensive therapy unit.

**Table 2. Model performance (randomly selected single patient admission for patients with multiple admissions)**

| Hospital | Missing values | N | AUC (95% CI) | Sensitivity % (95% CI) | Specificity % (95% CI) | PPV % (95% CI) | NPV % (95% CI) |
|---|---|---|---|---|---|---|---|
| **UHB - temporal validation** | | | | | | | |
| Median los calculated in diabetic patients only | mi | 6533 | 0.797 (0.785–0.810) | 69.5 (67.3–71.6) | 74.9 (73.7–76.2) | 51.3 (49.2–53.3) | 86.6 (85.6–87.7) |
| | Normal | 6533 | 0.808 (0.797–0.820) | 69.0 (66.8–71.1) | 77.1 (75.9–78.3) | 53.3 (51.3–55.4) | 86.7 (85.7–87.8) |
| **HEFT - external validation** | | | | | | | |
| Median los calculated in diabetic patients only | mi | 10690 | 0.758 (0.747–0.768) | 72.6 (70.9–74.2) | 66.0 (64.9–67.0) | 45.1 (43.7–46.5) | 86.2 (85.3–87.1) |
| | Normal | 10690 | 0.760 (0.750–0.770) | 69.2 (67.5–70.9) | 70.2 (69.1–71.2) | 47.2 (45.7–48.7) | 85.5 (84.7–86.4) |
| **Ipswich - external validation** | | | | | | | |
| Median los calculated in diabetic patients only | mi | 1885 | 0.736 (0.711–0.761) | 63.4 (59.1–67.6) | 69.3 (66.8–71.7) | 43.8 (40.3–47.5) | 83.4 (81.1–85.5) |
| | Normal | 1885 | 0.746 (0.722–0.770) | 62.5 (58.1–66.7) | 71.3 (68.9–73.7) | 45.2 (41.5–48.9) | 83.4 (81.2–85.5) |

Normal: missing blood test results replaced by values in the normal range; mi: missing blood test results replaced using multiple imputation.